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Predicting recessions: financial cycle versus term spread[1]

Claudio Borio, Mathias Drehmann and Dora Xia[2]

Abstract

Financial cycles can be important drivers of real activity, but there is scant evidence about how well they signal recession risks. We run a horse race between the term spread – the most widely used indicator in the literature – and a range of financial cycle measures. Unlike most papers, ours assesses forecasting performance not just for the United States but also for a panel of advanced and emerging market economies. We find that financial cycle measures have significant forecasting power both in and out of sample, even for a three-year horizon. Moreover, they outperform the term spread in nearly all specifications. These results are robust to different recession specifications.

JEL classifications: C33, E37, E44

Keywords: financial cycle, term spread, recession risk, panel probit model

[1] This paper is an extension of "The financial cycle and recession risk", *BIS Quarterly Review*, December 2018, by the same authors.

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Introduction

Predicting recessions has been a long-standing quest for market practitioners, policymakers and academics alike. As early as the first volume of *The American Economic Review*, Irving Fisher (1911) looked at developments in the "nation's bank book" to forecast the likelihood of a contraction in the United States.[3] Following Estrella and Mishkin (1998), a consensus has emerged that the inverted yield curve, ie long-term bond yields below short-term interest rates, is among the best signals of impending recessions, if not the best one.

The notion that finance in general – and financial cycles more specifically - matter for the real economy has regained significant attention after the Great Financial Crisis. A large and growing body of work supports this link. For one, there is substantial evidence that financial cycles, or their credit and asset price components, are helpful leading indicators of financial crises (eg Borio and Drehmann (2009), Schularick and Taylor (2012), Detken et al (2014)). These crises, in turn, generally usher in deep and protracted recessions (eg Jordà et al (2013)). Moreover, several studies have documented that credit booms weaken output in the medium run (eg Mian et al (2017), Lombardi et al (2017)), including by sapping productivity growth (Borio et al (2016)). And some recent work has begun to study the impact of financial conditions on risks to growth (eg Adrian et al (2018)).[4]

That said, research exploring how the financial cycle affects recession risk, ie the likelihood that a recession will occur in the near future, is scant. We fill this gap. As we rely on information from aggregate measures of domestic financial cycles, this study expands on the few papers in the literature that assess the predictive power of individual variables that proxy some aspects of the financial cycle, such as balance sheet conditions, property prices, credit growth or credit spreads (Liu and Mönch (2016), Christiansen et al (2017), Ponka (2017), Guender (2018)).

Moreover, in contrast to much of the literature, we assess the signalling power of the yield curve and financial cycle measures not only for the United States but also for an unbalanced panel of 16 advanced economies and nine emerging market economies (EMEs) from 1985 to 2017. This makes our results significantly more general. For instance, of the above-mentioned papers that look at variables related to the financial cycle, only Guender (2018) goes beyond the United States and considers a panel of European countries. And even the literature on the information content of the yield curve barely looks at EMEs; the exceptions are Mehl (2009), who examines the effect of the yield curve on growth; Öztürk and Pereira (2013), whose panel analysis includes EMEs; and several country-specific studies (eg Grabowski (2009) for Poland, Zulkhibri and Rani (2016) for Malaysia, and Paweenawat (2017) for Thailand)).

To ensure comparability with the literature, we run panel probit models. Following Berge and Jordà (2011), we rely on the area under the receiver operating characteristic (ROC) curve (AUC) to judge forecast performance. And we assess predictive performance both in and out of sample. Throughout, we compare the

[3] Fisher's starting point was the quantity theory of money, so he focused on bank deposits. But he also discussed the role of credit.

[4] See Claessens and Kose (2018) for a review of research exploring macro-financial linkages.

performance of the financial cycle with that of the term spread, taken as the benchmark.

In in-sample tests, financial cycle measures perform generally better than the term spread. When the competing variables are considered on a standalone basis, AUCs for financial cycle measures are statistically significantly higher and are significant even for a three-year horizon, for which the term spread is uninformative. When financial cycle measures and the term spread are included jointly in a probit model, they all remain statistically significant up to a two-year horizon. But combining information from the spread and financial cycle measures improves only marginally, and not significantly, AUCs and other evaluation metrics relative to specifications that include just financial cycle measures.

This superior performance also applies to the out-of-sample tests. Here, we carry out two exercises to assess the indicators' predictive content in (quasi) real time. We examine first the effect of real-time data[5] and fixed model parameters estimated using our first 10 years of data. We then assess the combined effect of real-time data and model parameters estimated recursively. In both exercises, and in contrast to the term spread, the financial cycle measures retain statistically significant forecasting power. Most likely, the reason for the disappointing performance of the term spread is that, for several countries, the variable is "contaminated" by credit risk premia. As a result, in some episodes, the yield curve steepened rather than flattened ahead of recessions, including in some periphery countries ahead of the 2011–12 euro sovereign debt crisis. By contrast, the financial cycle measures are immune to this problem.[6] Consistently with this explanation, the term spread retains forecasting information for the United States.

The outperformance of financial cycle proxies is robust regardless of whether we forecast the likelihood that the economy will be in a recession at a *specific* point in time several periods ahead – the literature standard – or whether the business cycle will turn *within* the next few periods. Following much of the literature (eg Rudebusch and Williams (2009)), in the main text we focus on the first approach – in our case one, two or three years ahead. As an alternative, we estimate the risk that the business cycle will turn from boom to bust within the next one, two or three years. This second type of exercise is much closer to the spirit of Irving Fisher, who had observed in 1911: "The exact date of such crisis (recession in his context), of course, it would be foolish to predict, but it if it occurs it would seem likely to occur between, say 1913 and 1916" (Fisher (1911), p 304).

The rest of the paper is structured as follows. In the first section, we briefly introduce the notion of the financial cycle and document how the nature of the business cycle, and its link with the financial cycle, have changed in the past 50 years. In the second section, we explain our methodology. In the third, we evaluate the performance of financial cycle proxies and compare it with that of the term spread based on full-sample information, ie ex post. In the fourth, we consider out-of-sample

[5] For the data, we would ideally use real-time releases. However, these are not available for the panel, so we use quasi-real-time information, ie we take the latest data vintage and calculate the financial cycle and normalise all variables using data only up to that point.

[6] The zero (effective) lower bound and unconventional monetary policy may affect the term spread's informational content to forecast recession risk, as the lower bound constrains short rates and unconventional monetary policy depresses the term premium in long rates. For a discussion, see Coroneo and Pastorello (2017), Fendel et al (2018) and the minutes of the Federal Open Market Committee (March 2019) for examples.

exercises, seeking to mimic the information policymakers have when assessing risks in real time, ie ex ante. In the fifth, we consider a different definition of recession risk as robustness check. Then we conclude.

The financial cycle and recession risk: a look at the data

The term "financial cycle" refers to the self-reinforcing interactions between perceptions of value and risk, risk-taking, and financing constraints (Borio (2014)). Typically, rapid increases in credit drive up property and asset prices, which in turn increase collateral values and thus the amount of credit the private sector can obtain until, at some point, the process goes into reverse. Historically, this mutually reinforcing interaction between financing constraints and perceptions of value and risks has tended to cause serious macroeconomic dislocations.

The financial cycle can be approximated in different ways (Aikman et al (2015), Claessens et al (2012) or Drehmann et al (2012)). Empirical research suggests that, especially if one is interested in episodes that have proven more damaging for economic activity, a promising strategy is to capture it through *medium-term* fluctuations in credit and property prices. This can be done in terms of individual series or, preferably, a combination thereof. We therefore rely on a "composite" financial cycle proxy similar to that in Drehmann et al (2012).

In addition, we assess the usefulness of the debt service ratio (DSR), defined as interest payments plus amortisation divided by GDP. Drehmann et al (2018) find a strong link between debt accumulation and subsequent debt service, which in turn has a large negative effect on growth. Moreover, Juselius and Drehmann (2019) show that the financial cycle can be described by the joint behaviour of leverage and the DSR.

Given the uncertainties in measuring financial cycles, we also explore alternative financial cycle proxies, including the credit-to-GDP gap, the property price gap and medium-term growth rates in the credit-to-GDP ratio. Appendix 2 shows that these proxies do not perform as well as the composite financial cycle indicator or the DSR. Yet they still outperform the forecast performance of the term spread, in particular for the two- and three-year horizons.[7]

Previous research has identified two important features of the financial cycle.[8] First, financial cycle peaks tend to coincide with banking crises or considerable financial stress. This is not surprising. During expansions, the self-reinforcing interaction between financing constraints, asset prices and risk-taking can overstretch balance sheets, making them more fragile and sowing the seeds of the subsequent financial contraction. This, in turn, can drag down the economy and put further stress on the financial system.

Second, the financial cycle can be much longer than the business cycle. Business cycles as traditionally measured have tended to last up to eight years, and financial cycles around 15–20 years since the early 1980s. The difference in length means that

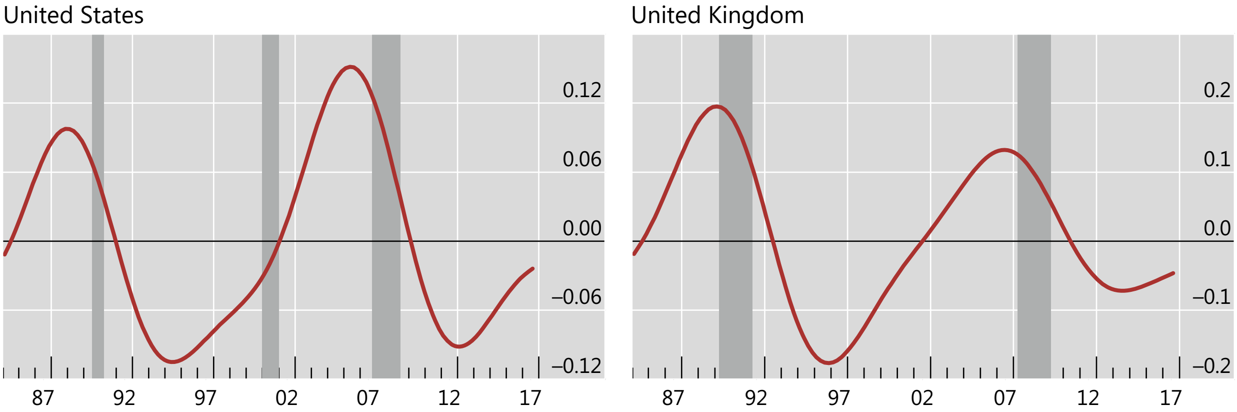
[7] We do not examine the forecasting power of credit spreads for predicting recessions because the measure is not available for many of the countries we consider.

[8] See eg Drehmann et al (2012), Claessens et al (2012) and Aikman et al (2015).

a financial cycle can span more than one business cycle. As a result, while financial cycle peaks tend to usher in recessions, not all recessions are preceded by such peaks.

A first look at the relationship between the composite financial cycle proxy and recessions in the United States and the United Kingdom since the early 1980s illustrates these points (Graph 1). Financial cycle booms took place ahead of recessions in the early 1990s and the late 2000s. At the same time, the shallow recession in the early 2000s in the United States did not coincide with a financial cycle peak: while the economy slowed and equity prices tanked, the financial expansion – as measured by credit and property prices – continued, only to reverse a few years later, triggering the Great Recession. By contrast, in the United Kingdom, no actual recession took place in the early 2000s, so that the two recessions coincided with the two financial cycle peaks.

Financial cycles tend to boom ahead of recessions[1] Graph 1



The shaded areas represent recessions.

[1] Financial cycles are measured by the composite financial cycle proxy calculated from frequency-based (bandpass) filters capturing medium-term cycles in real credit, the credit-to-GDP ratio and real house prices.

A longer-term cross-country perspective reveals an interesting change in the nature of recessions.[9] Graph 2 documents the behaviour of key variables in the five years around business cycle turning points in our sample of 16 advanced economies (vertical lines). In the period 1970–84 (blue lines), inflation and the short-term interest rate tended to increase by several percentage points ahead of cyclical peaks and term spreads to plunge and become highly negative (first three panels). At the same time, there was little sign of a financial boom (fourth panel). By contrast, since 1985 (red lines), around business cycle peaks inflation has been lower and remarkably stable, the short-term interest rate has increased only modestly and the term spread has narrowed far less. Correspondingly, strong financial cycle expansions have been very

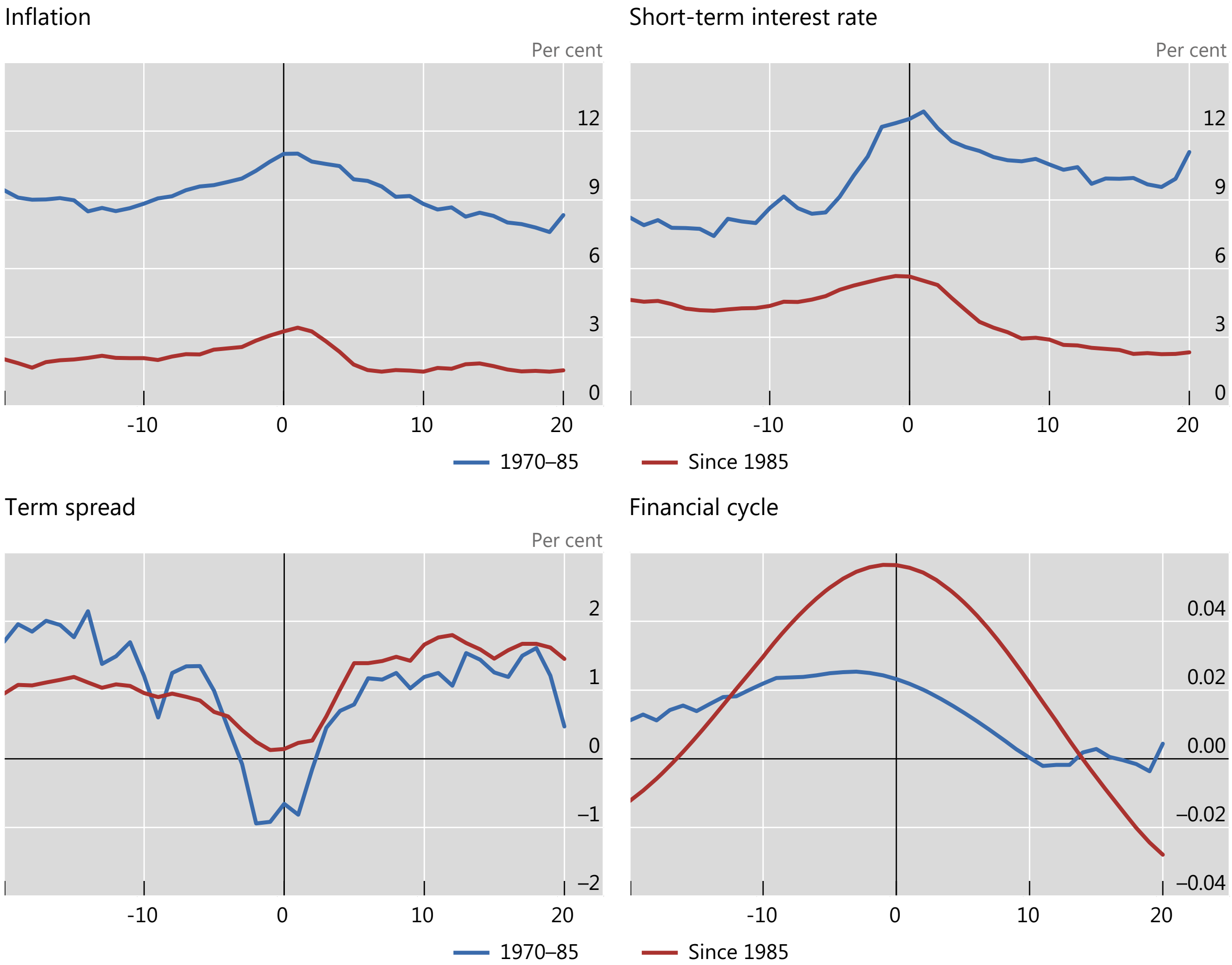
[9] Interestingly, the recessions since the early 1980s have come to resemble those that were the norm under the pre-World War I classical gold standard (eg Huffman and Lothian (1984)) and in the run-up to the Great Depression in the 1920s (Eichengreen and Mitchener (2003)). This was the previous globalisation era; like today's, it was also characterised by price stability and a high degree of both trade and financial integration. See BIS (2018).

much in evidence. One could say that there has been a shift from inflation-induced[10] to financial cycle-induced recessions.

The changing nature of the business cycle[1]

Average of the variables indicated over the selected period

Graph 2



[1] The horizontal axis denotes quarters around recessions in the business cycles, with the peak date set at zero (vertical lines). Lines show the median evolution across the advanced economies in our sample and events in the respective time period.

Why this is the case is less clear. But three changes deserve particular attention. First, financial markets were liberalised starting in the 1980s. Without sufficient prudential safeguards, this change is likely to have allowed greater scope for the self-reinforcing interactions at the heart of the financial cycle to play out. Second, starting roughly at the same time, inflation-focused monetary regimes became the norm. And the evolving thinking of central banks led them to gradually downplay the role of monetary and credit aggregates. This meant that central banks had little reason to tighten monetary policy if inflation remained low, even as financial imbalances built up. Finally, from the 1990s on, the entry of China and former communist countries into the world economy, alongside the international integration of product markets

[10] Zarnowitz (1999) uses the term "central bank recession" to refer to the common view that recessions are always driven by monetary policy tightening.

and technological advances, boosted global supply and strengthened competitive pressures, sapping labour's and firms' pricing power. Coupled with greater central bank credibility, this arguably made it more likely that inflationary pressures would remain muted even as expansions gathered pace. It also meant that financial booms could build up further and that a turn in the financial cycle, rather than rising inflation and the consequent monetary tightening, would trigger an economic downturn.[11]

Data and methodology

The previous graphical evidence is highly suggestive of the information that financial cycle proxies can convey about recession risk. In addition, it provides two indications for our more formal empirical analysis. For one, because of the changing nature of the business cycle, it makes sense to start our tests in 1985. In addition, because financial cycles build up gradually, it is appropriate to focus on medium-term horizons in addition to the short-term ones common in the literature. We therefore aim to predict recessions up to three years ahead.

We use quarterly data for 16 advanced economies from 1985 to 2017.[12] In general, we only include a country if all explanatory variables are available. A few countries therefore enter the sample later, mostly because of a lack of data for the term spread.[13]

To assess the broader validity of the results, we also look at quarterly data for nine EMEs.[14] For these, data start in 1996 at the earliest and more often around 2000. One limiting factor is that government bond markets were less developed before then, constraining the sample for the term spread. In addition, property prices are scarcer for earlier dates, limiting the ability to compute the composite financial cycle proxy. In the case of EMEs, therefore, we do not use a homogeneous panel.[15] While we still show results for the composite financial cycle proxy for comparability, these should be treated as indicative given the short time series.

To define recession dates, we follow the most widely used procedure. We take the recession dates from the National Bureau of Economic Research (NBER) or the Economic Cycle Research Institute. These rely on expert judgment based on the behaviour of several variables, such as output and employment. When such recession dates are not available, we rely on a standard business cycle-dating algorithm that

11 For a discussion of changes in policy regimes and their implications for monetary and financial stability, see eg Borio and Lowe (2002) and Borio (2016).

12 Our sample comprises Australia, Belgium,* Canada, Finland,* France, Germany, Ireland,* Italy, Japan, the Netherlands,* Norway,* Spain, Sweden, Switzerland, the United Kingdom and the United States. For countries marked with an asterisk, we date business cycles using a business cycle-dating algorithm.

13 The term spread is constraining the sample for Australia (1986), Finland (1988) and Norway (1988). The DSR is constraining the sample for Ireland (2002).

14 Brazil, the Czech Republic, Hungary, Korea, Malaysia, Poland, Russia, South Africa and Thailand. For these countries, we always date business cycles using a business cycle-dating algorithm. For an EME to be included, we require that all three variables are available and that we have at least 10 years of spread and DSR data. In addition, we only include an EME if we observe at least one recession in the sample.

15 The sample is homogeneous for regressions with the DSR and the term spread.

identifies peaks and troughs in real GDP (Harding and Pagan (2002)). We do not consider degrees of intensity: either a recession occurs (*R=1*) or it does not *(R=0)*. This, of course, means that countries with, on average, higher trend growth rates may experience fewer recessions but as many and equally sizeable slowdowns in growth. This is less of an issue for advanced economies.

For the main analysis, we follow most of the literature and predict whether the economy is in a recession h periods ahead ($S_{i,t,h} = R_{i,t+h} = 1$) based on the state of explanatory variables ($X_{i,t}$) at time t. Hence, in the panel probit setup we estimate:

$$Prob\left(S_{i,t,h} = 1 | X_{i,t}\right) = \Phi(\alpha_h + \beta_h{}' X_{i,t}) \qquad (1)$$

To judge forecast performance, we calculate several measures, although in the main text we rely on the ROC curve (Berge and Jordà (2011)). This curve maps out all possible combinations of type I errors (missed recessions) and type II errors (false alarms). The AUC provides a convenient and easily interpretable summary measure of the indicator's signalling quality.[16] A completely uninformative indicator has an AUC of 0.5 – like tossing a coin; and a perfect one an AUC of 1 – all recessions predicted, no false alarms. The AUC of an informative indicator falls in between and is statistically different from 0.5.

To ensure comparability with the existing literature, we also report other standard measures, such as the mean absolute error (MAE), the root mean square error (RMSE) and the log probability score (LPS) (eg Rudebusch and Williams (2009)). As the main insights do not change, we report these in Annex Table A2.1.

We perform both in-sample and out-of-sample exercises. The in-sample estimation sheds light on the tightness of the link between the variables and recessions with the benefit of hindsight (ex post); the out-of-sample analysis evaluates their performance in real time, ie taking into account only the information available up to that point (with the caveat that the latest data vintage instead of the real-time release is used). The latter is a more stringent and useful test, since it replicates the information available to policymakers when they form a judgment on the risks. Because of data limitations, we limit the out-of-sample exercise to advanced economies.

We look at several explanatory variables.

The term spread. We define it as the difference between the 10-year government bond rate and the three-month money market rate. The interest rates are from Bloomberg.

The composite financial cycle indicator. We follow Drehmann et al (2012), who use bandpass filters with frequencies from eight to 32 years to extract medium-term

16 A probability can be transformed into a binary indicator, which is equal to 1 ("on") if it is above a critical threshold *T*, and zero ("off") otherwise. A type I error (missed call) occurs if the binary indicator is "off" but a recession follows; and a type II error (false alarm) if it is "on" but no recession follows. By changing the critical threshold *T,* the fraction of type I and type II errors changes. Technically, there is no direct mapping between the significance of coefficients in the probit equation and the AUC, especially if the probit includes more than one variable. In that case, the probit regression coefficients may be statistically significant, even if their inclusion does not change the AUC much.

cyclical fluctuations in real (inflation-adjusted) credit, the credit-to-GDP ratio and real property prices, which are then averaged to derive a composite measure of the financial cycle. We modify the approach slightly by applying the filter directly to the log level of the individual series instead of filtering the growth rates.[17]

The debt service ratio. This measures interest payment and amortisation of the private non-financial sector relative to income. The BIS publishes data on debt service ratios from 1999 onwards (Drehmann et al (2015)). We extend them backwards using the same methodology.

As all these variables differ in terms of levels and volatility across countries, we standardise them by their mean and standard deviation.[18]

In-sample results

As much of the literature focuses on the United States, we present results for this country first and then consider the panel of countries.

It is already evident from the raw data that the term spread provides useful information about the likelihood that the US economy will be in a recession (Annex Graph A2.1, left-hand panel). Unsurprisingly, and as expected from the literature, across all horizons the estimated coefficient is highly statistically significant and negative (Table 1). And the AUCs are very high, up to 0.93 for a one-year horizon (Graph 3).

Predicting that the economy is in a recession *h* periods ahead: United States

Regression coefficients from probit models — Table 1

Horizon		Financial cycle	DSR	Term spread	Financial cycle and term spread	DSR and term spread
1 year	Financial cycle	0.51***			0.29*	
	DSR		2.38***			1.81***
	Spread			-1.51***	–1.41***	–1.14***
2 years	Financial cycle	0.53***			0.33*	
	DSR		0.59***			0.02
	Spread			–1.04***	–0.91***	–1.02***
3 years	Financial cycle	0.43**			0.36**	
	DSR		0.14			–0.14
	Spread			–0.41***	–0.33**	–0.48**

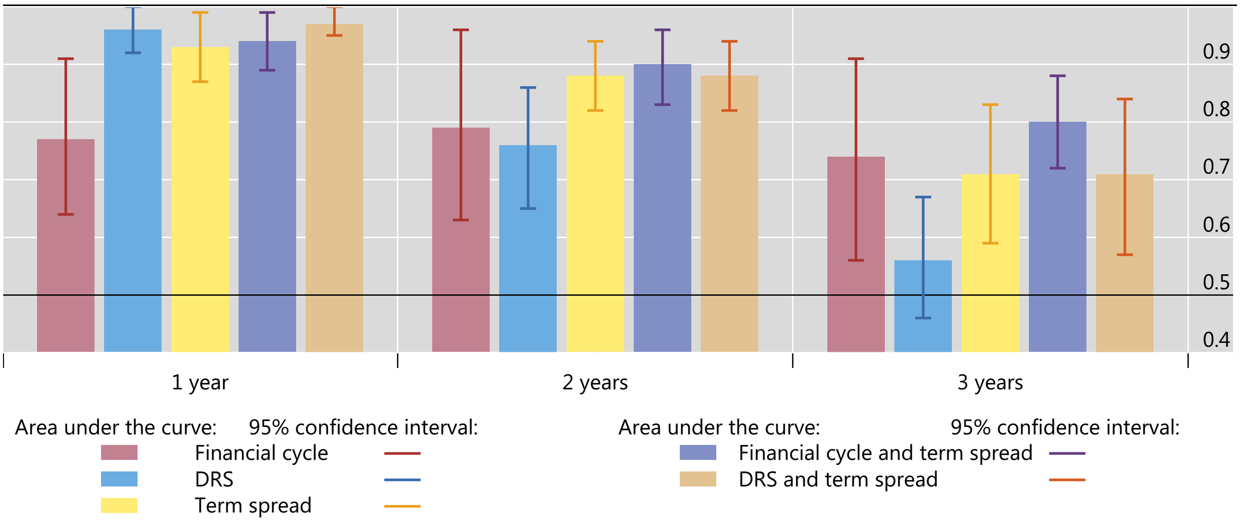
The table reports estimated coefficients from probit regressions (equation (1)) for advanced economies and emerging market economies, respectively; ***/**/* indicates significance at the 1/5/10% level.

[17] We take the data for total credit, credit-to-GDP ratios and long-run property prices from BIS statistics.

[18] This has the additional benefit of implicitly controlling for fixed effects in a similar way to Chamberlain's random effects probit model.

That said, the financial cycle indicators are also powerful, in particular the DSR. For a one-year forecast horizon, the DSR actually outperforms the term spread slightly (AUC of 0.96)[19] and is insignificantly different from 1 – the perfect indicator (Graph 3). Again, this is evident from the raw data (Annex Graph A2.1, right-hand panel).

AUCs for different forecast horizons: United States | Graph 3



The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

Combing the term spread and financial cycle proxies boosts forecast performance at all horizons. But the gain is very limited in comparison with the spread alone.

The results for the United States should be taken with a large pinch of salt, however. As our sample begins in 1985, we observe only three recessions, with a total of 14 quarters when the economy was in a recession. Hence the need to consider the evidence for a broader set of countries.

The in-sample results for the panel confirm that the financial cycle measures provide valuable information for recessions.

This conclusion is evident for advanced economies, for which a richer sample is available, and regardless of the forecasting horizon. Coefficients for the composite financial cycle measure or the debt service burden are always highly statistically significant (Table 1, first two columns).[20]

[19] The AUCs of the DSR and the term spread are not significantly different statistically.

[20] We obtain standard errors by block-bootstrapping in order to account for cross-country correlations.

Predicting that the economy is in a recession *h* periods ahead: global

Regression coefficients from panel probit models — Table 2

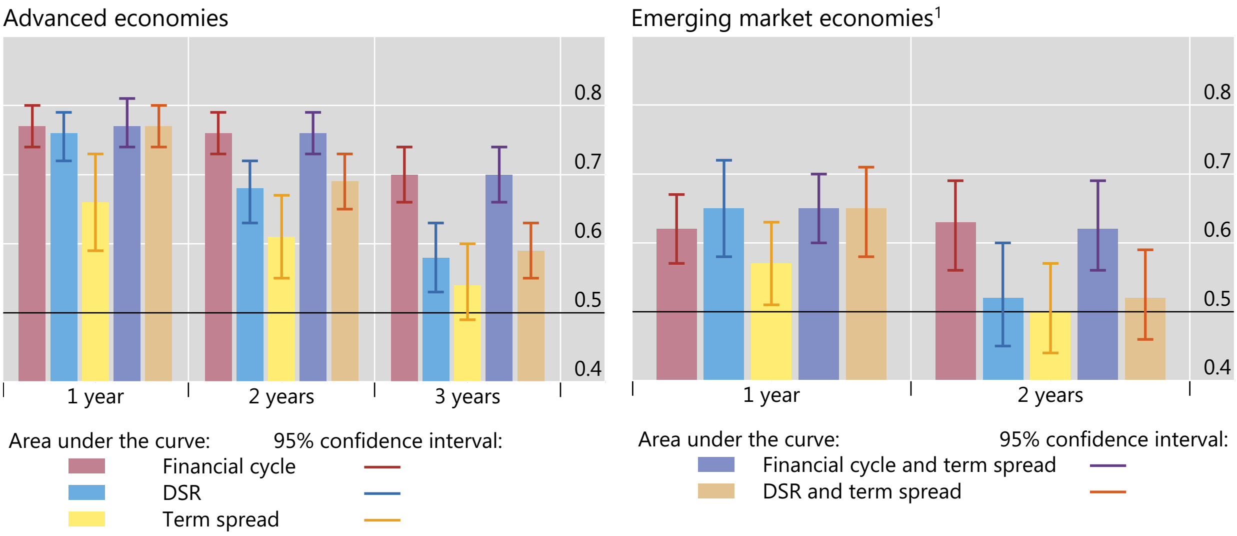
Horizon		Financial cycle	DSR	Term spread	Financial cycle and term spread	DSR and term spread
Advanced economies						
1 year	Financial cycle	0.69***			0.62***	
	DSR		0.61***			0.57***
	Spread			−0.35***	−0.21***	−0.28***
2 years	Financial cycle	0.63***			0.60***	
	DSR		0.38***			0.35***
	Spread			−0.23***	−0.09*	−0.17***
3 years	Financial cycle	0.43***			0.44***	
	DSR		0.16***			0.15***
	Spread			−0.08	0.03	−0.06
Emerging market economies[1]						
1 year	Financial cycle	0.24***			0.24***	
	DSR		0.25***			0.23***
	Spread			−0.12**	−0.18**	−0.03
2 years	Financial cycle	0.24***			0.24***	
	DSR		0.02			0.05
	Spread			0.06	0.02	0.07

The table reports estimated coefficients from probit regressions (equation (1)) for advanced economies and emerging market economies, respectively; ***/**/* indicates significance at the 1/5/10% level.

[1] No three-year forecast horizons for EMEs, due to the limited sample.

AUCs for different forecast horizons: global

Graph 4



The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

[1] No three-year forecast horizons for EMEs, due to the limited sample.

In comparison, the term spread seems to be useful only for evaluating recession risk one and two years ahead. The coefficients and AUCs are not statistically significant at the three-year horizon (Table 1, upper panel, third column; and Graph 4, left-hand panel, yellow bars).

Moreover, even at one- and two-year horizons, the composite financial cycle and DSR outperform the term spread. Their AUCs are higher, and the difference is statistically significant.

That said, the financial cycle proxies and the term spread seem to provide complementary information. When they are included jointly in a probit model, they all remain statistically significant up to a two-year horizon. Accordingly, AUCs and other evaluation metrics improve (Table 1, upper panel, fourth and fifth columns; and Graph 4, left-hand panel, purple and orange bars). The improvement, though, is not statistically significant. And at the three-year horizon, the gain is negligible.

As noted above, while the generally weaker performance of the term spread in the panel may come as a surprise, it reflects, at least in part, the role of the credit risk premium in the yield curve outside the United States. In particular, when we remove the euro area periphery countries (ie Ireland, Italy and Spain), the AUCs of the term spread increase to 0.71 and 0.65 at the one- and two-year forecasting horizons, respectively. Even then, however, the term spread continues to have less forecasting power than the composite financial cycle indicator or the DSR, whose information content is little affected.

The strong performance of the financial cycle proxies is all the more remarkable given that the methodology stacks the deck against finding significant predictive power. Since the financial cycle, as defined here, tends to be longer than the business cycle, we cannot expect booms to precede all recessions – there will be misses. And because the financial cycle builds up and recedes slowly (eg Graph 1), it is likely to sound several "false alarms" before and after the recession has ended. Hence, from the start, the benchmark for the AUC cannot be expected to be 1, ie the AUC of the perfect indicator.

The results for EMEs broadly mirror those for advanced economies. Financial cycle proxies are informative, albeit less so than in advanced economies. Coefficients and AUCs are always statistically significant, regardless of forecast horizon. The exception is the DSR, which yields the highest AUC at the one-year horizon but is not significant at the two-year one (Table 2, lower panel, second column; and Graph 4, right-hand panel). Despite less developed bond markets, term spreads also seem to provide some valuable information at the one-year horizon (Table 2, lower panel, third column). This is in line with the finding by Mehl (2009).

Out-of-sample results

We perform two exercises to assess the indicators' performance in real time from 1995 onwards: we first examine the effect of (quasi) real-time data, and then the combined effect of (quasi) real-time data and model parameters estimated recursively, ie by adding one observation at a time.

We can use only quasi-real-time data, as real-time releases are not available for the panel we look at. But the effects may be limited. For the spread, real-time data are not an issue, as market data are not revised. In addition, in many countries credit data are also not revised substantially (Drehmann and Tsatsaronis (2014)). Nonetheless, real-time data will affect the DSR and the composite financial cycle indicator through revisions to income, GDP and property prices. As such, our quasi-real-time data only account for the changes in the mean and standard deviation by which variables are normalised. Moreover, we calculate the composite financial cycle indicator recursively, only accounting for information up to that quarter.

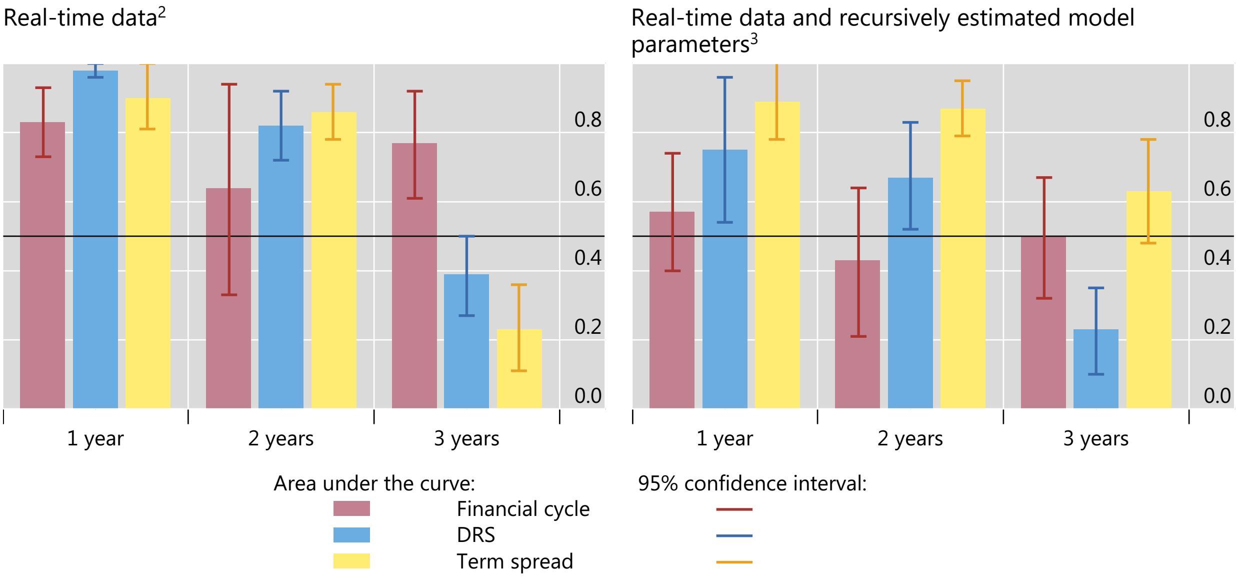
To assess the impact of (quasi) real-time data only, we estimate the models up to Q1 1995 and keep the parameters fixed when forecasting.

To assess the combined effect of real-time data and time-varying model parameters, we re-estimate the models each period a forecast is made (again starting from Q1 1995) and use the resulting coefficients and real-time data to forecast.

For both cases, thus, the out-of-sample forecast performance is based on the sample from Q1 1995 to Q4 2017.

As above, we first discuss the United States before turning to the panel. We do not consider the specifications with multiple predictors in the case of the United States because we end up with a very limited sample.

Out-of-sample AUCs: United States[1] Graph 5



The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

[1] We start the forecasting exercise in Q1 1995. [2] Forecasts are calculated using real-time data and fixed parameters estimated with data up to Q1 1995. [3] Forecasts are calculated using real-time data and recursively estimated model parameters, ie by adding one observation at a time.

Even using real-time data, the forecast performance of the financial cycle proxies in the United States is very strong, in particular that of the DSR (Graph 5, left-hand panel). The AUC for a one-year horizon is 0.98 and remains large and significant also at the two-year horizon (0.82).[21] The term spread also performs well out of sample, as its out-of-sample forecast performance is the same as the full-sample one. The

[21] In fact, using the subsample before 1995, the DSR predicts recessions at a one-year horizon perfectly (with infinite β_h in the probit model or equivalently a step function).

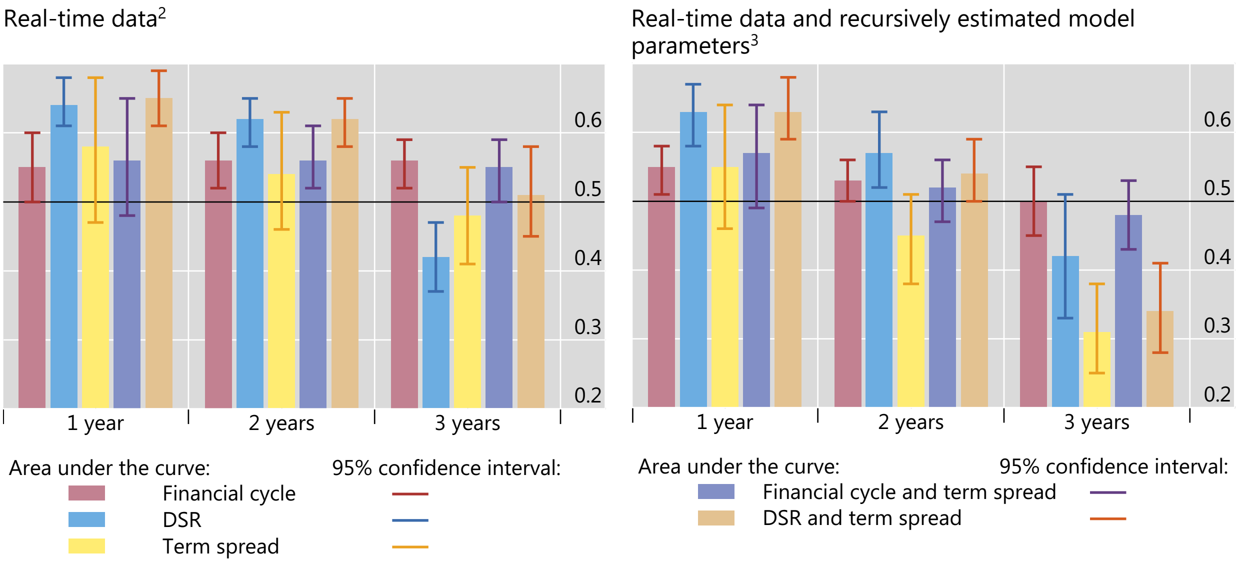
robustness of the US results is remarkable given that the training sample contains only one recession. That said, the sample is even more limited than for the full-sample US results, naturally raising questions about robustness.

The out-of-sample panel results for the financial cycle measures mirror the insights for the United States. They continue to have high forecasting power and deliver AUCs statistically significantly higher than 0.5 (Graph 6, left-hand panel). The AUC of the DSR is above 0.6 up to the two-year horizon. While AUCs for the composite financial cycle are lower than in the full-sample estimation, their performance is still statistically significant.[22]

In contrast, the AUCs of the term spread are not statistically significant. The signal is statistically indistinguishable from that of an uninformative indicator. The contrast to the results for the United States confirms that credit risk premia are the key factor behind this result.

Allowing for changes in model parameters does not alter the broad message (Graph 6, right-hand panel). Both financial cycle proxies deliver AUCs that are statistically higher than 0.5 up to a two-year horizon, although not beyond. In comparison, AUCs from the term spread do not differ from that of a random indicator at all horizons. Interestingly, allowing parameter estimates to vary as the sample size increases seems to reduce forecast accuracy to some extent: the AUCs obtained when parameters are fixed are slightly higher.

Out-of-sample AUCs: global[1] Graph 6



The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

[1] We start the forecasting exercise in Q1 1995. [2] Forecasts are calculated using real-time data and fixed parameters estimated with data up to Q1 1995. [3] Forecasts are calculated using real-time data and recursively estimated model parameters, ie by adding one observation at a time.

[22] Dropping individual countries does not significantly change the AUCs for the out-of-sample results. The only exception is that, for a one-year horizon, the AUC of the DSR increases to 0.72 when Japan is dropped.

Predicting turning points

For robustness, we look at the forecasting power of the financial cycle and the term spread for assessing the likelihood that the cycle will turn from boom to bust (ie a recession starts) within the next one, two or three years. In comparison with our analysis in the main text, this forecasting exercise differs along two key dimensions.

First, it focuses on pre-recession periods only. In the previous exercise, when we estimate the likelihood that the economy will be in a recession, the sample contains many observations for which the machine is "predicting" a recession *when the economy is already in one*. For instance, for a one-year prediction horizon, in our sample 50% of the observations followed by a recession in four quarters are times when the economy is already in a recession. While this is standard in the literature, it is of less value for policymakers and practitioners.

Second, this definition does not impose a strict lead-lag relationship on the data. Instead, the interest is on whether a recession will begin within a given interval of time.

To operationalise this recession indicator, one question is how to treat recession periods. Following the early warning indicator literature for financial crises, we drop them. The reason is that setting the indicator to 0 during this interval would bias the results (Borio and Lowe (2002), Bussière and Fratzscher (2006)).

As the three-year forecasting window is quite long, we are also interested to see to which year the forecasting power applies.[23] Hence, we consider one, two and three years ahead separately. This in turn raises the question of how to treat observations within the three-year forecast horizon of interest but outside the exact estimation window. In other words, how should one treat economically correct signals (eg a negative spread) that are issued within the three-year horizon (eg two years ahead) but outside the window of interest (eg whether he recession will start the following year)? In our earlier analysis, these signals would be considered "wrong" given the strict lead-lag relationship, despite being correct economically. To overcome this problem, we follow Drehmann and Juselius (2014) and ignore the informational content of the variables within the three-year horizon but not within the one-, two- or three-year horizon considered.

Accordingly, we define an indicator variable $I_{i,h,t}$=1 one, two or three years before the beginning of a recession. We do not consider information during recessions and in the two years before recessions that are outside the estimation horizon of interest: in all other periods, $I_{i,h,t}$=0.

To clarify the differences between the two different recession risk measures, Annex Table A2.2 provides an example of the two approaches for different horizons around the recession in the United States starting in 2007.

Similarly to the main analysis, we use a panel probit model to predict the probability of a recession starting within the next h periods. Specifically, we have:

$$Prob\left(I_{i,h,t} = 1 | X_{i,t}\right) = \Phi(\alpha_h + \beta_h{}' X_{i,t}) \qquad (2)$$

[23] We also ran exercises with the whole three-year forecasting horizon. The results again confirm the message from the main analysis. The results are available upon request.

Both in-sample and out-of-sample results confirm the message of the main analysis. Financial cycle proxies contain valuable information in evaluating recession risks; and they tend to outperform the term spread (Annex Table A2.3; Annex Graphs A2.2 and A2.3).

Interestingly, across the variables and the different forecast horizons, there are no major differences between the AUCs for predicting whether the recession will start any time within a given horizon or whether the economy will be in recession in a specific quarter ahead. To be sure, point estimates differ. For instance, the full-sample AUC of the financial cycle is higher and that of the DSR lower when predicting the turning point. Yet confidence bands generally overlap, so that differences are not statistically significant. This is reassuring, as most practitioners and commentators use the results of the literature mainly when the economy is still in boom and not yet in a recession.

Conclusion

Business cycles may not die of old age (Rudebusch (2016)), but if financial booms develop, they become more fragile. This is the case in both advanced economies and emerging market economies. Moreover, given that financial cycles build up slowly, the corresponding proxies provide information about recession risk even at a three-year horizon. And when we run a horse race against the term spread – the indicator most widely used to assess recession risk – we find that they outperform the term spread in both in-sample and out-of-sample exercises. The debt service ratio is particularly effective in this respect. These results suggest that financial cycle proxies may be another indicator that could be useful to policymakers, professional forecasters and market participants more generally.

References

Adrian, T, F Grinberg, N Liang and S Malik (2018): "The term structure of growth-at-risk", *IMF Working Papers*, no WP/18/180, August.

Aikman, D, A Haldane and B Nelson (2015): "Curbing the credit cycle", *The Economic Journal*, vol 125, no 585, pp 1072–109.

Bank for International Settlements (2018): *Annual Economic Report 2018*, Chapter I, June.

Berge, T and O Jordà (2011): "Evaluating the classification of economic activity into recessions and expansions", *American Economic Journal: Macroeconomics*, vol 3, no 2, pp 246–77.

Borio, C (2014): "The financial cycle and macroeconomics: what have we learnt?", *Journal of Banking & Finance*, vol 45, pp 182–98, August. Also available as *BIS Working Papers*, no 395, December 2012.

——— (2016): "Monetary and prudential policies at a crossroads? New challenges in the new century", *BIS Working Papers*, no 216, September.

Borio, C and M Drehmann (2009): "Assessing the risk of banking crises – revisited", *BIS Quarterly Review*, March, pp 29–46.

Borio, C , E Kharroubi, C Upper and F Zampolli (2016): "Labour reallocation and productivity dynamics: financial causes, real consequences", *BIS Working Papers*, no 534, January.

Borio, C and P Lowe (2002): "Asset prices, financial and monetary stability: exploring the nexus", *BIS Working Papers*, no 114, July.

Bussière, M and M Fratzscher (2006): "Towards a new early warning system of financial crises", *Journal of International Money and Finance*, vol 25, no 6, pp 953–73.

Christiansen, C, J Eriksen and S Møller (2017): "Metro Area common house price declines and US recessions", September.

Claessens, S and M Kose (2018): "Frontiers of macrofinancial linkages", *BIS Papers*, no 95, January.

Claessens, S, M Kose and M Terrones (2012): "How do business and financial cycles interact?", *Journal of International Economics*, vol 87, no 1, pp 178–90.

Coroneo, L and S Pastorello (2017): "European spreads at the interest rate lower bound", unpublished manuscript.

Detken, C, O Weeken, L Alessi, D Bonfim, M Boucinha, C Castro, S Frontczak, G Giordana, J Giese, N Jahn, J Kakes, B Klaus, J-H Lang, N Puzanova and P Welz (2014): "Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options", European Systemic Risk Board, *Occasional Papers*, no 5.

Drehmann, M and C Borio (2009): "Towards an operational framework for financial stability: "fuzzy" measurement and its consequences, *BIS Working papers*, no 284, June.

Drehmann, M, C Borio and K Tsatsaronis (2012): "Characterising the financial cycle: don't lose sight of the medium term!", *BIS Working Papers*, no 380, June.

Drehmann, M, A Ilnes, M Juselius and M Santos (2015). "How much income is used for debt payments? A new database for debt service ratios." *BIS Quarterly Review*, September, pp 89–103.

Drehmann, M and M Juselius (2014): "Evaluating early warning indicators of banking crises: satisfying policy requirements", *International Journal of Forecasting*, vol 30, no 3, pp 759–80.

Drehmann, M, M Juselius, and A Korinek (2018): "Going with the flows: new borrowing, debt service and the transmission of credit booms", *NBER Working Papers*, no 24549.

Drehmann, M, K Tsatsaronis (2014): "The credit-to-GDP gap and countercyclical capital buffers: questions and answers", *BIS Quarterly Review*, March, pp 55–73.

Drehmann, M and J Yetman (2018): "Why you should use the Hodrick-Prescott filter – at least to generate credit gaps", *BIS Working Papers*, no 744, September.

Eichengreen, B and K Mitchener (2003): "The Great Depression as a credit boom gone wrong", in S Wolcott and C Hanes (eds), *Research in Economic History*, vol 22, Emerald Group Publishing Limited, pp 183–237.

Estrella, A and F Mishkin (1998): "Predicting US recessions: financial variables as leading indicators", *Review of Economics and Statistics*, vol 80, no 1, pp 45–61.

Fendel, R, N Mai and O Mohr (2018): "Recession probabilities for the Eurozone at the zero lower bound", *WHU Working Paper Series in Economics*, no 18/04.

Fisher, I (1911): "The equation of exchange, 1896–1910", *The American Economic Review*, vol 1, no 2, pp 296–305.

Grabowski, S (2009): "The financial indicators leading real economic activity – the case of Poland", *Central European Journal of Economic Modelling and Econometrics*, vol 4, no 1, pp 311-32.

Guender, A (2018): "Credit prices vs credit quantities as predictors of economic activity in Europe: which tell a better story?", *Journal of Macroeconomics*, no 57, pp 380−99.

Hamilton, J (2018): "Why you should never use the Hodrick-Prescott filter", *Review of Economics and Statistics*, vol 100, no 5, pp 831–43.

Harding, D and A Pagan (2002): "Dissecting the cycle: a methodological investigation", *Journal of Monetary Economics*, vol 49, no 2, pp 365–81.

Huffman, W and J Lothian (1984): "The gold standard and the transmission of business cycles, 1833–1932", in D Bordo and A Schwartz (eds), *A retrospective on the classical gold standard*, NBER, pp 1821–931.

Jordà, Ò, M Schularick and A Taylor (2013): "When credit bites back", *Journal of Money, Credit and Banking*, vol 45, no s2, pp 3–28.

Juselius, M and M Drehmann (2019): "Leverage dynamics and the burden of debt", *Oxford Bulletin of Economics and Statistics*, forthcoming.

Liu, W and E Mönch (2016): "What predicts US recessions?", *International Journal of Forecasting*, vol 32, no 4, pp 1138−50.

Lombardi, M, M Madhusudan and I Shim (2017): "The real effects of household debt in the short and long run", *BIS Working Papers*, no 607, January.

Mehl, A (2009): "The yield curve as a predictor and emerging economies", *Open Economies Review*, vol 20, no 5, pp 683–716.

Mian, A, A Sufi and E Verner (2017): "Household debt and business cycles worldwide", *The Quarterly Journal of Economics*, vol 132, no 4, pp 1755–817.

Öztürk, H and L Pereira (2013): "Yield curve as a predictor of recessions: evidence from panel data", *Emerging Markets Finance and Trade*, vol 49, pp 194–212.

Paweenawat, A (2017): "The information content of the term structure of interest rates in emerging economies: the case of Thailand", *Journal of Emerging Market Finance,* vol 16, no 2, pp 136–50.

Ponka, H (2017): "The role of credit in predicting US recessions", *Journal of Forecasting*, vol 36, no 5, pp 469–82.

Rudebusch, G (2016): "Will the economic recovery die of old age?", Federal Reserve Bank of San Francisco, *Economic Letters*, February.

Rudebusch, G and J Williams (2009): "Forecasting recessions: the puzzle of the enduring power of the yield curve", *Journal of Business and Economic Statistics*, vol 27, no 4, pp 492–503.

Schularick, M and A Taylor (2012): "Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008", *American Economic Review*, vol 102, no 2, pp 1029–61.

Zarnowitz, V (1999): "Theory and history behind business cycles: are the 1990s the onset of a golden age?", *Journal of Economic Perspectives*, vol 13, no 2, pp 69–90.

Zulkhibri, M and M Rani (2016): "Term spread, inflation and economic growth in emerging markets: evidence from Malaysia", *Review of Accounting and Finance*, vol 15, no 3, pp 372–92.

Annex 1: Alternative financial cycle measures

In addition to the composite financial cycle measure and the DSR, we also examine credit and property price developments separately. In the broad sense, this is akin to looking at the subcomponents of the financial cycle.

To capture medium-term credit developments, we use the credit-to-GDP gap as proposed by Borio and Lowe (2002) and used in Basel III, ie we take the difference between the credit-to-GDP ratio and its one-sided Hodrick-Prescott (HP) filtered trend with a smoothing parameter, λ, of 400,000.[24] In addition, we consider medium-term growth rates in the credit-to-GDP ratio, a popular measure in literature (eg Mian et al (2017) or Jordà et al (2013)). We report the results for the three-year growth rate only, but five-year growth rates perform similarly.

We also consider the property price gap. This is calculated in similar fashion, by taking the deviation of real residential property prices from their one-sided HP-filtered trend with $\lambda = 400{,}000$ (eg Drehmann and Borio (2009)).

Both in-sample and out-of-sample results suggest that these financial cycle measures are informative in assessing recession risks in panel analysis. This is consistent with the previous literature that focuses mainly on the United States. For advanced economies, all three measures are statistically significant in panel probit regressions and their AUCs are statistically significantly higher than 0.5 in sample (Table A1.1, upper panel, first three columns; and Graph A1.1, left-hand panel, red, yellow and blue bars). For the credit gap, the AUCs are statistically significant up to a two-year horizon even out of sample (Graph A1.2, yellow bars). For EMEs, the growth rate in the credit-to-GDP ratio remains a robust recession predictor, while the credit and property gaps become less informative (Table A1,1, lower panel, first three columns; and Graph A1.1, right-hand panel, red, yellow and blue bars).

Similar to the financial proxies examined in our main analysis, these alternative financial cycle measures seem to provide complementary information to the term spread. They all remain statistically significant when they are included in a probit model with the term spread (Table A1.1, last three columns). Accordingly, AUCs improve, albeit not statistically significant (Graphs A1.1 and A1.2, purple, orange and grey bars).

While these alternative financial cycle measures are useful for assessing recession risks, they are less informative than the composite financial cycle proxy in our main analysis. None of them can deliver in-sample AUCs that are statistically significant for *both* advanced economies *and* emerging market economies, or that are so out of sample for advanced economies up to a two-year horizon.

[24] Hamilton (2018) argues that an HP filter should never be used because it results in spurious dynamics, it has end-point problems, and its typical implementation is at odds with its statistical foundations. Yet, as Drehmann and Yetman (2018) argue, in the absence of clear theoretical foundations, all proposed credit gaps are just indicators. They also show that, for financial crisis prediction, the credit-to-GDP gaps derived by a one-sided HP filter outperform the gaps based on linear projections as suggested by Hamilton. Credit-to-GDP gaps are available from the BIS website.

Predicting that the economy is in a recession *h* periods ahead: alternative financial cycle measures

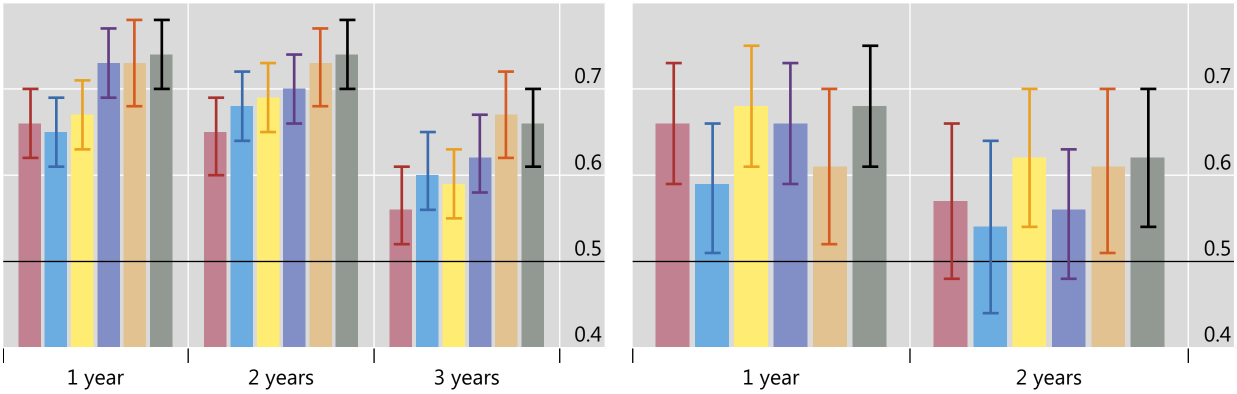
Regression coefficients from panel probit models — Table A1.1

Horizon		Credit gap	Property price gap	Three-year credit growth	Credit gap and term spread	Property price gap and term spread	Three-year credit growth and term spread
				Advanced economies			
1 year	Credit gap	0.33***			0.40***		
	Property price gap		0.30***			0.32***	
	Three-year credit growth			0.34***			0.42***
	Term spread				–0.41***	–0.38***	–0.39***
2 years	Credit gap	0.32***			0.43***		
	Property price gap		0.36***			0.46***	
	Three-year credit growth			0.37***			0.49***
	Term spread				–0.25***	–0.19**	–0.24***
3 years	Credit gap	0.14***			0.26***		
	Property price gap		0.21***			0.36***	
	Three-year credit growth			0.18***			0.33***
	Term spread				–0.13*	–0.13	–0.11
				Emerging market economies			
1 year	Credit gap	0.38***			0.39***		
	Property price gap		–0.24*			–0.40***	
	Three-year credit growth			0.41***			0.40***
	Term spread				0.06	–0.48**	–0.06
2 years	Credit gap	0.19*			0.17		
	Property price gap		–0.13			–0.33**	
	Three-year credit growth			0.27***			0.27***
	Term spread				–0.10	–0.53**	–0.08

The table reports estimated coefficients from probit regressions for advanced economies and emerging market economies, respectively; ***/**/* indicates significance at the 1/5/10% level.

AUCs for different forecast horizons: alternative financial cycle measures, global Graph A1.1

Advanced economies | Emerging market economies



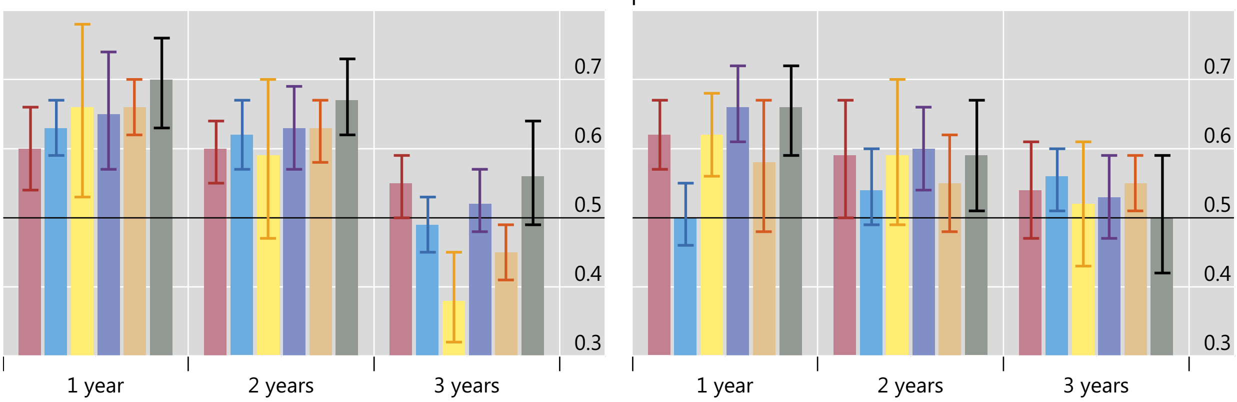
Area under the curve: Credit gap; Property price gap; 3-year credit growth; Credit gap and term spread; Property price gap and term spread; 3-year credit growth and term spread

95% confidence interval: Credit gap; Property price gap; 3-year credit growth; Credit gap and term spread; Property price gap and term spread; 3-year credit growth and term spread

The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

Out-of-sample AUCs for different forecast horizons: alternative financial cycle measures, global[1] Graph A1.2

Real-time data[2] | Real-time data and recursively estimated model parameters[3]



Area under the curve: Credit gap; Property price gap; 3-year credit growth; Credit gap and term spread; Property price gap and term spread; 3-year credit growth and term spread

95% confidence interval: Credit gap; Property price gap; 3-year credit growth; Credit gap and term spread; Property price gap and term spread; 3-year credit growth and term spread

The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

[1] We start the forecasting exercise in Q1 1995. [2] Forecasts are calculated using real-time data and fixed parameters estimated with data up to Q1 1995. [3] Forecasts are calculated using real-time data and recursively estimated model parameters, ie by adding one observation at a time.

Annex 2: Supplementary tables and graphs

Alternative measures to evaluate forecast performance

Table A2.1

		Financial cycle[1]	DSR	Term spread	Financial cycle and term spread	DSR and term spread
				Advanced economies		
1 year	MAE	0.24	0.25	0.24	0.27	0.23
	RMSE	0.35	0.36	0.35	0.37	0.35
	LPS	0.40	0.41	0.40	0.45	0.39
2 years	MAE	0.25	0.28	0.28	0.29	0.25
	RMSE	0.36	0.38	0.38	0.39	0.38
	LPS	0.42	0.45	0.45	0.47	0.41
3 years	MAE	0.28	0.30	0.30	0.30	0.28
	RMSE	0.38	0.39	0.39	0.39	0.38
	LPS	0.45	0.48	0.48	0.49	0.45
				Emerging market economies		
1 year	MAE	0.28	0.26	0.27	0.27	0.26
	RMSE	0.37	0.37	0.37	0.37	0.37
	LPS	0.45	0.43	0.44	0.45	0.43
2 years	MAE	0.26	0.26	0.26	0.26	0.26
	RMSE	0.37	0.37	0.37	0.37	0.37
	LPS	0.44	0.44	0.44	0.44	0.44

The table reports various measures of forecast accuracy for probit models: the mean absolute error (MAE), the root mean squared error (RMSE) and the log probability score (LPS). They are calculated as defined in Rudebusch and Williams (2009).

[1] Financial cycles are measured by the composite financial cycle proxy.

Definition of the recession risk for main analysis and robustness check: the US example

Table A2.2

		Main analysis: Predict that the economy is in a recession in h periods $S_{i,t,h}$			Robustness check: Predict that a recession will start within in h periods $I_{i,t+h}$		
Year	Recession	h = 1 year	h = 2 years	h = 3 years	h = 1 year	h = 2 years	h = 3 years
....							
2004 Q2		0	0	0	0	0	0
2004 Q3		0	0	0	0	0	0
2004 Q4		0	0	1			1
2005 Q1		0	0	1			1
2005 Q2		0	0	1			1
2005 Q3		0	0	1			1
2005 Q4		0	1	1		1	
2006 Q1		0	1	1		1	
2006 Q2		0	1	1		1	
2006 Q3		0	1	0		1	
2006 Q4		1	1	0	1		
2007 Q1		1	1	0	1		
2007 Q2		1	1	0	1		
2007 Q3		1	0	0	1		
2007 Q4	1	1	0	0			
2008 Q1	1	1	0	0			
2008 Q2	1	1	0	0			
2008 Q3	1	0	0	0			
2008 Q4	1	0	0	0			
2009 Q1	1	0	0	0			
2009 Q2	1	0	0	0			
2009 Q3		0	0	0	0	0	0
2009 Q4		0	0	0	0	0	0
etc.							

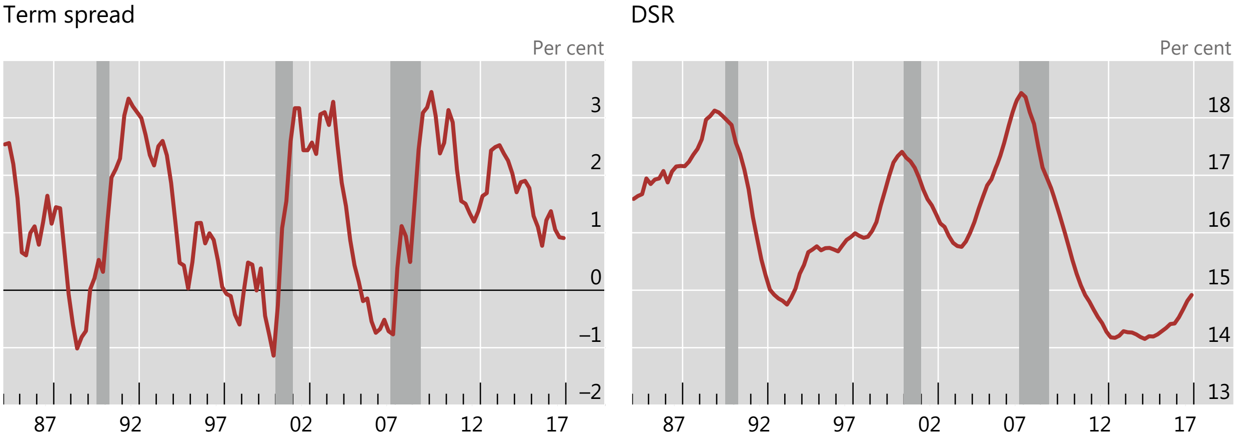
Predicting that a recession will start within *h* periods: global

Regression coefficients from panel probit models — Table A2.3

Horizon		Financial cycle	DSR	Term spread	Financial cycle and term spread	DSR and term spread
			Advanced economies			
1 year	Financial cycle	0.95***			0.90***	
	DSR		0.57***			0.52***
	Spread			–0.45***	–0.38***	–0.41***
2 years	Financial cycle	0.83***			0.84***	
	DSR		0.34***			0.33***
	Spread			–0.27***	–0.29***	–0.26***
3 years	Financial cycle	0.53***			0.53***	
	DSR		0.02			0.01
	Spread			–0.15**	–0.16**	–0.15**
			Emerging market economies			
1 year	Financial cycle	0.24***			0.24***	
	DSR		0.34***			0.32***
	Spread			–0.14	–0.11	–0.08
2 years	Financial cycle	0.17			0.19**	
	DSR		0.15			0.14
	Spread			–0.10	–0.16	–0.08

The table reports estimated coefficients from probit regressions (equation (2)) for advanced economies and emerging market economies, respectively; ***/**/* indicates significance at the 1/5/10% level.

Term spread tends to invert and DSR to boom ahead of recessions: United Sates — Graph A2.1

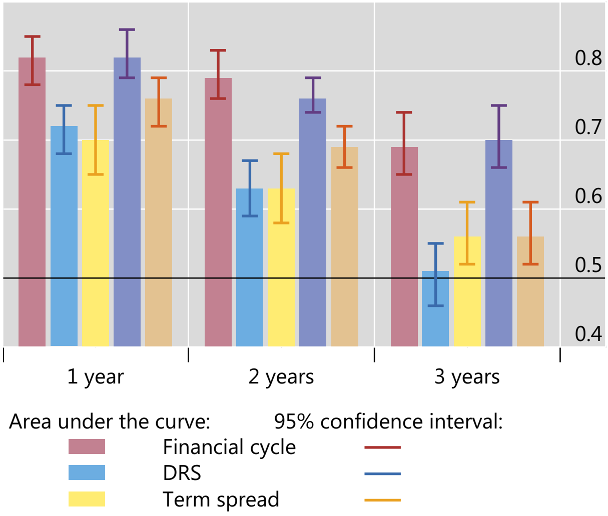


The shaded areas represent recessions.

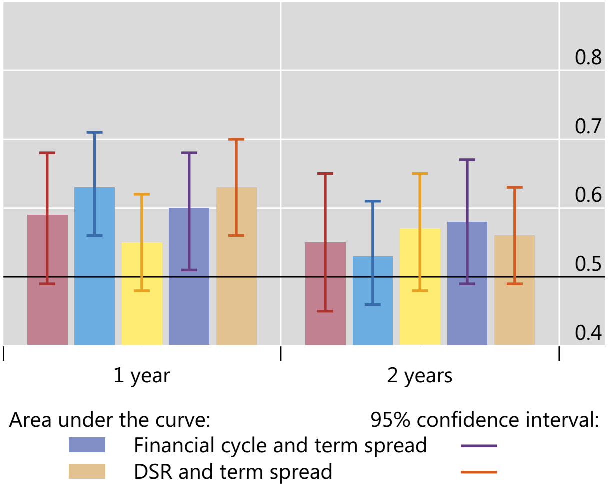
AUCs for predicting that a recession will start within *h* periods: global

Graph A2.2

Advanced economies



Emerging market economies

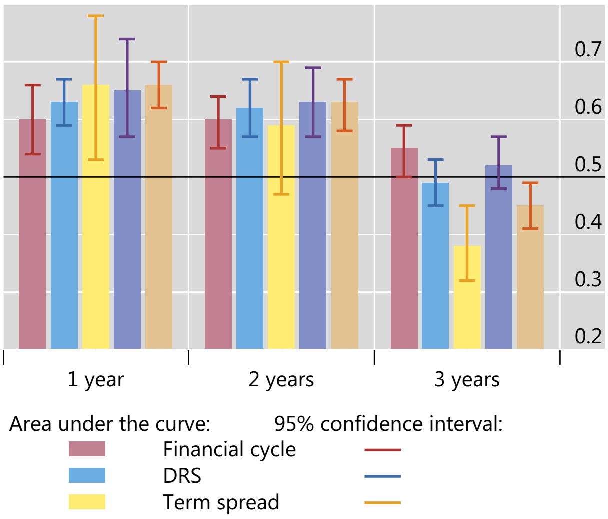


The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

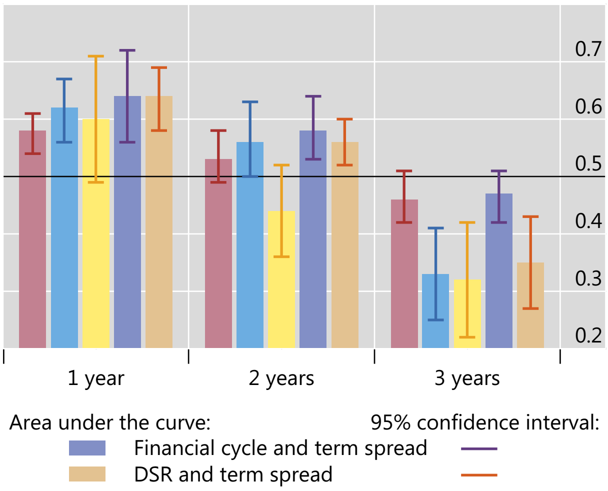
Out-of-sample AUCs predicting that a recession will start within *h* periods: advanced economies[1]

Graph A2.3

Real-time data[2]



Real-time data and recursively estimated model parameters[3]



The horizontal lines at 0.5 indicate the area under the curve of an uninformative, random variable.

[1] We start the forecasting exercise in Q1 1995. [2] Forecasts are calculated using real-time data and fixed parameters estimated with data up to Q1 1995. [3] Forecasts are calculated using real-time data and recursively estimated model parameters, ie by adding one observation at a time.

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